Deutsches Institut für
Wirtschaftsforschung

DIW BERLIN

Discussion Papers

1009

Guglielmo Maria Caporale • Roman Matousek •
Chris Stewart

EU Banks Rating Assignments: Is there Heterogeneity between New and Old Member Countries?

Berlin, June 2010

IMPRESSUM

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin
Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
http://www.diw.de

ISSN print edition 1433-0210
ISSN electronic edition 1619-4535

Available for free downloading from the DIW Berlin website.

Discussion Papers of DIW Berlin are indexed in RePEc and SSRN.
Papers can be downloaded free of charge from the following websites:

http://www.diw.de/de/diw_01.c.100406.de/publikationen_veranstaltungen/publikationen/diskussionspapiere/diskussionspapiere.html
http://ideas.repec.org/s/diw/diwwpp.html
http://papers.ssrn.com/sol3/JELJOUR_Results.cfm?form_name=journalbrowse&journal_id=1079991

EU Banks Rating Assignments: Is there Heterogeneity between New and Old Member Countries?

Guglielmo Maria Caporale[1]
Roman Matousek[2]
Chris Stewart[3]

Abstract

We model EU countries' bank ratings using financial variables and allowing for intercept and slope heterogeneity. Our aim is to assess whether "old" and "new" EU countries are rated differently and to determine whether "new" ones are assigned lower ratings, *ceteris paribus*, than "old" ones. We find that country-specific factors (in the form of heterogeneous intercepts) are a crucial determinant of ratings. Whilst "new" EU countries typically have lower ratings than "old" ones, after controlling for financial variables we also discover that all countries have significantly different intercepts, confirming our prior belief. This intercept heterogeneity suggests that each country's rating is assigned uniquely, after controlling for differences in financial factors, which may reflect differences in country risk and the legal and regulatory framework that banks face (such as foreclosure laws). In addition, we find that ratings may respond differently to the liquidity and operating expenses to operating income variables across countries. Typically ratings are more responsive to the former and less sensitive to the latter for "new" EU countries compared with "old" EU countries.

Keywords: EU countries, banks, ratings, ordered probit models, index of indicator variables

JEL Classification: C25, C51, C52, G21.

[1] Corresponding author. Research Professor at DIW. Centre for Empirical Finance, Brunel University, West London, UB8 3PH, UK. Email: Guglielmo-Maria.Caporale@brunel.ac.uk
[2] Centre for International Capital Markets, London Metropolitan Business School, London Metropolitan University, 84 Moorgate, London, EC2M 6SQ. Tel: 020-7320-1569. E-mail: r.matousek@londonmet.ac.uk.
[3] London Metropolitan Business School, London Metropolitan University, 84 Moorgate, London, EC2M 6SQ. Tel: 020-7320-1651. E-mail: c.stewart@londonmet.ac.uk.

1. Introduction

Ratings of banks and companies conducted by External Credit Assessment Institutions (ECAIs) may be seen as instruments that provide investors with *prima facie* information about the financial position of the subject in question and on the price of credit risk.

Ratings are ordinal measures that should not only reflect the current financial position of sovereign nations, firms, banks, etc. but also provide information about their future financial positions. The objective of our paper is to analyse the determinants of individual bank ratings conducted by Fitch Ratings (FR) and to investigate whether the country of origin matters for individual ratings. For this purpose, we first consider whether (and which of) the key financial variables of banks reflect individual ratings (that is, according to FR, a key component for long- and short-term rating). Second, we examine whether bank ratings are systematically determined by the country origin of commercial banks. Our first hypothesis is that FR might assign higher ratings to commercial banks from "old" EU countries that have the same financial position as those from "new" EU countries. This could reflect differences in country risk (given that bank ratings cannot exceed sovereign ratings) or differences in legal and regulatory factors (including their enforcement), such as foreclosure laws. Another hypothesis is that FR might set ratings differently for "old" and "new" EU countries in terms of response to financial factors. That is, the coefficients on financial variables in a regression explaining ratings may be different for "old" and "new" EU countries.

In other words, we test if commercial banks from "new" EU countries are assigned ratings on the basis of their financial ratios in the same way as "old" EU countries or if other factors are considered. To this end, we incorporate "new" EU and country-specific indicator variables to capture heterogeneous variations in ratings under the rationale that a bank's rating is related to the country in which it is based. For country-specific indicators we construct index-of-indicator variables that are in the spirit of the method applied in Hendry (2001) and Hendry and Santos (2005), although we extend it to allow heterogeneous country slopes. Caporale et al. (2009) applied a similar methodological approach, within the context of modelling bank ratings, by allowing country-specific intercepts. Our extension to permit country-specific slopes is a further contribution to current research in this field. We also assess the predictive power of our model to classify the individual ratings of the commercial banks in question.

The ability to predict the financial soundness of banks, corporations and sovereign countries has been of central importance for analysts, regulators and policy makers. A large number of studies have employed financial ratios to predict failures of individual firms (banks), for example, Altman et al. (1977) and Ohlson (1980). Models that predict bank failures using so-called Early Warning Systems (EWS) have appeared in a number of studies, including Mayer and Pifer (1970) and Kolari et al. (2002). Within this context, the financial variables of commercial banks have been utilised in several ways.

Yet the ability of ECAIs to assign ratings correctly has been extensively questioned (Altman and Saunders, 1998, Levich et al., 2002, Altman and Rijken, 2004, Amato and Furfine, 2004, Portes, 2008). One of the most frequent arguments about the prediction abilities of rating agencies (RAs) is that they could provide misleading information since the analysis is backward- rather than forward-looking. In addition, the low transparency of ratings assignments contributes to the concern over the accuracy of ratings. Further, ECAIs do not have, and cannot have, superior information to market participants about uncertainty and the degree of insolvency (illiquidity) of companies. By modelling ratings we seek to identify their determinants and, using measures of fit, gauge how transparent ratings assignments are. In particular, we assess the extent to which ratings are determined by a bank's financial position and, using indicator variables, ascertain the extent to which rating assignments reflect differences in a bank's country of origin.

There are numerous studies that predict bond ratings such as Kamstra et al. (2001), who utilise ordered-logit regression. Other recent studies (Kim, 2005; Huang et al., 2004 and Lee, 2007) show that artificial intelligence methods do not provide superior predictions of bond ratings compared with standard ordered-choice methods.[4] Hence, using ordered logit/probit regressions is a valid way of addressing the main challenge in modelling ratings, which is to increase the probability of correct classifications. However, we are not aware of any previous studies that seek to model and predict individual *bank* ratings allowing for heterogeneous country effects (in both intercept and slope), which is the aim of this paper.

The organization of the paper is as follows. Section 2 describes the data and the methods applied, while Section 3 discusses the principal empirical findings. The last section concludes.

[4] There is also extensive research on credit risk ratings migration, see, for example, Feng et al. (2008), and Stefanescu et al. (2009).

2. Data and Methodology

We model the individual ratings of EU banks as produced by Fitch Ratings (FR). These ratings are divided into six main categories (A, B, C, D, E, F) which, with four intermediate subdivisions (A/B, B/C, C/D, D/E), give ten categories of bank performance. We use 1168 ratings observations for 303 different European banks, denoted Y_i, between 1996 and 2008.[5] Y_i is ordinal and has ten categories that are assigned integer values, 0 to 9: lower values indicate a lower rating. The ten rating categories are: F (0), E (1), D/E (2), D (3), C/D (4), C (5), B/C (6), B (7), A/B (8), A (9).

We apply ordered-choice estimation techniques to model this ordinal dependent variable because, as is well known, they are the appropriate method to use in this case. The ordered dependent variable model assumes the following latent variable form (see Greene, 2008):

$$Y_i^* = \sum_{k=1}^{K} \beta_k X_{ki} + u_i \qquad \textbf{(1)}$$

where X_{ki} is the kth explanatory variable for the ith bank, u_i is a stochastic error term, and Y_i^* is the unobserved dependent variable that is related to the observed dependent variable, Y_i, (assuming ten categories) as follows:

[5] On average there are 3.85 (approximately 4) different time-series observations for each bank (some ratings in our sample change while others are simply confirmed). This suggests that the sample may not be independent: there may be bank specific factors that affect each bank in all time periods. To the extent that such factors are omitted from our model they will enter the model's error term. If such factors are uncorrelated with the variables included in the model the strict exogeneity assumption will not be violated and the estimator will not become inconsistent from this source. However, if these omitted factors are correlated with the model's covariates this will induce inconsistency in the estimator. To guard against this we try to minimise the likelihood of there being omitted variables by incorporating the financial covariates previously considered in the literature and by adding a country index to account for country-specific factors that affect a bank. However, we do not incorporate individual intercepts (essentially fixed effects) for each bank because this can cause inconsistency in the estimator when the number of time-series observations per bank is small, due to the incidental parameters problem – see Greene (2008).

$$
\begin{aligned}
&Y_i = 1 \quad \text{if } Y_i^* \le \lambda_1 \\
&Y_i = j \quad \text{if } \lambda_{j-1} < Y_i^* \le \lambda_j, \quad j = 2,3,\ldots,9 \\
&Y_i = 10 \quad \text{if } \lambda_9 < Y_i^*
\end{aligned}
\qquad \textbf{(2)}
$$

where λ_1, λ_2,…, λ_9 are unknown limit points to be estimated with the coefficients (the β_k s). We are primarily interested in the general direction of correlation between the dependent and independent variables. Therefore, we use the sign of β_k to provide guidance on whether the estimated signs of the coefficients are consistent with our *a priori* expectations. This is instead of looking at the marginal effects which indicate the direction of change of the dependent variable (for each value of the dependent variable) in response to a change in X_{ki}. For ordered-choice models these marginal effects are difficult to interpret.

The probit form of this model assumes that the cumulative distribution function employed is based upon the standard normal, while the logit form assumes a logistic distribution. Greene (2008) suggests that probit and logit models yield results that are very similar in practice and so we focus on one form, namely the probit form.

The first explanatory variable that we consider is the year in which the rating was made [$Date_i$]. This is 3 in 1996, 4 in 1997, 5 in 1998 and so on.[6] The second set of covariates considered is the first *lagged* values of the following seven financial variables: the ratio of equity to total assets [denoted $Equity_i$], the ratio of liquid assets to total assets [$Liquidity_i$], the natural logarithm of total assets [$\ln(Assets)_i$], the net interest margin $[NIM_i]$, the ratio of operating expenses to total operating income [OE_OI_i], other operating income to total assets, $[OOIA_i]$ and the return on assets [ROA_i].[7] Current values of financial variables are not used as they may contain information not known when the rating was

[6] Originally we had data from 1994 where 1994 took the value of 1. However, data prior to 1996 was lost due to missing observations on some variables.
[7] Some other variables were considered but were omitted from the analysis due to multicollinearity.

made.[8] A further benefit of using lagged financial variables is that it ensures that they are exogenous and no endogeneity bias will affect the estimates.[9] The choice of variables is guided by the past literature.

A third set of variables employed are country indicator (or dummy) variables. Two broad types of indicators are considered. First, we construct a shift dummy variable, D_i^{New}, that is defined to take the value of unity for the 12 "new" EU countries and is zero for the 15 "old" EU countries.[10] This dummy variable, multiplied by the pth financial variable, Z_{pi}, yields the shift in that variable's slope coefficient for a "new" EU country, $Z_{pi}^{New} = Z_{pi} \times D_i^{New}$, where, $p = 1,2,...,7$.[11] Second, we develop index-of-indicator variables that allow each country to have different intercept and slope coefficients. However, an ordered-choice model incorporating 27 dummy variables for each covariate cannot be estimated; hence, we employ a method that is in the spirit of Hendry (2001) and Hendry and Santos (2005) to construct indices-of-indicator variables for each covariate.

To construct a country index for the intercept we estimate two probit models, one incorporating "new" EU countries' dummies and one for "old" EU countries' dummies. That is, one probit regression of ratings on the 12 "new" EU countries' (intercept) dummy variables, D_{mi}, $\mathrm{m} = 1,2,...,12$, is estimated, thus:[12]

$$\hat{Y}_i^* = \sum_{m=1}^{12} \hat{\delta}_m D_{mi} \tag{3}$$

where, D_{mi} takes the value of one for a bank in country m and is zero otherwise and $\hat{\delta}_m$ denotes the respective estimated coefficients.

---

[8] For example, if a bank's rating was decided in January 2007 then the value of any explanatory factor measured over the whole of 2007 would be unknown when the rating was made.

[9] Not only are the financial covariates predetermined, the other covariates are also exogenous: the time variable is deterministic and the country index (discussed below) is constructed as a linear combination of deterministic country dummy variables (which are also deterministic). The use of lagged variables to avoid endogeneity is a strength of our work relative to some other authors who have used contemporaneous financial covariates when modelling ratings.

[10] The twelve "new" EU countries in our sample (associated with the fifth enlargement of the EU) are: Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia. The fifteen "old" EU countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the UK.

[11] There are 7 financial variables.

[12] Including all 27 countries' dummy variables in one regression was not possible due to problems with estimating the model, hence the use of two separate regressions for "new" and "old" EU countries' dummy variables. Note that both regressions use all 1168 observations.

The initial index for "new" EU countries is constructed as the sum of the products of the coefficients and their corresponding dummy variables for the statistically significant terms, thus:

$$I_i^N = \sum_{m=1}^{12} \hat{\delta}_1 D_{mi} \tag{4}$$

Similarly, the following ordered-choice model is fitted to the 15 "old" EU country dummy variables, D_{mi}, $\mathrm{m} = 13,14,...,27$:

$$\hat{Y}_i^* = \sum_{m=13}^{27} \hat{\delta}_m D_{mi} \tag{5}$$

The initial index for "old" EU countries is correspondingly constructed as:

$$I_i^O = \sum_{m=13}^{27} \hat{\delta}_1 D_{mi} \tag{6}$$

To obtain a preliminary index for all countries, ratings are then regressed on these two indices, thus:

$$\hat{Y}_i^* = \hat{\gamma}_N I_i^N + \hat{\gamma}_O I_i^O \tag{7}$$

The initial country index is constructed as:

$$I_i^C = \hat{\gamma}_N I_i^N + \hat{\gamma}_O I_i^O \tag{8}$$

This index was checked for appropriateness by running a single regression that included the initial country index plus one individual country's dummy, that is:

$$\hat{Y}_i^* = \hat{\lambda} I_i^C + \hat{\alpha}_m D_{mi} \tag{9}$$

If the latter individual dummy variable was significant the value of its coefficient, $\hat{\alpha}_m$, was incorporated into the country index. This was repeated for all 27 countries, that is, 27 regressions containing only two variables (the country index and a particular country's dummy) were estimated. After all the coefficients of the individual country dummies that were significant in these 27 regressions had been incorporated into the index this step was repeated until no individual country dummies were significant at the 5% level (when included in a regression with the country index). The result is the intercept country index – reported in Table 4.[13]

A modified procedure was employed to construct indices for the non-intercept covariates. For each covariate (except for $Date_i$) and slope interaction variables, Z^C_{pmi}, for each country were constructed using:

$$Z^C_{pmi} = Z_{pi} \times D_{mi} \qquad \textbf{(10)}$$

For the p[th] financial covariate, one regression is estimated using the "new" EU countries' slope interaction variables. That is, ratings is regressed on the 7 financial variables, date and the 12 "new" EU countries' slope interaction terms for the p[th] variable, thus:[14]

$$\hat{Y}_i^* = \hat{\beta}_1 Date_i + \sum_{p=1}^{7} \hat{\phi}_p Z_{pi} + \sum_{m=1}^{12} \hat{\theta}_m Z^C_{pmi} \qquad \textbf{(11)}$$

A corresponding regression for the p[th] financial variable is estimated using slope interaction variables of 15 "old" EU countries, as:

$$\hat{Y}_i^* = \hat{\beta}_1 Date_i + \sum_{p=1}^{7} \hat{\phi}_p Z_{pi} + \sum_{m=13}^{27} \hat{\theta}_m Z^C_{pmi} \qquad \textbf{(12)}$$

Initial indices for the p[th] covariate for "new" and "old" EU countries, respectively, are constructed using only the statistically significant interaction terms in each regression (equations **(11)** and **(12)**), as:

[13] Using an index of indicators to model country-specific factors in our model of ratings ensures that these country factors do not enter the disturbance term of this model. To the extent that there is some correlation between these country-specific terms and the financial covariates the inclusion of this country indicator in the model prevents endogeneity that could otherwise arise from this source.
[14] We do not include interaction terms for all 27 countries in one regression due to problems with estimating the model.

$$I_{pi}^{N} = \sum_{m=1}^{12} \hat{\theta}_m Z_{pmi}^{C} \quad \textbf{(13)}$$

$$I_{pi}^{O} = \sum_{m=13}^{27} \hat{\theta}_m Z_{pmi}^{C} \quad \textbf{(14)}$$

To obtain a preliminary index of the pth covariate for all countries we regress ratings on these two indices, thus:

$$\hat{Y}_i^* = \hat{\omega}_N I_{pi}^{N} + \hat{\omega}_O I_{pi}^{O} \quad \textbf{(15)}$$

The initial country slope index for the pth financial variable is constructed as:

$$I_{pi}^{C} = \hat{\omega}_N I_{pi}^{N} + \hat{\omega}_O I_{pi}^{O} \quad \textbf{(16)}$$

This index was refined by the following iterative process. A single regression that included the date, the financial variables, the initial country slope index plus a single interaction term for country m and the pth financial variable was estimated as follows:

$$\hat{Y}_i^* = \hat{\beta}_1 Date_i + \sum_{p=1}^{7} \hat{\phi}_p Z_{pi} + \hat{\rho} I_{mi}^{C} + \hat{\mu}_{pm} Z_{pmi}^{C} \quad \textbf{(17)}$$

If the latter individual interaction term was significant the value of its coefficient, $\hat{\mu}_{pm}$, was incorporated into the country index. This was repeated for all 27 countries. After all the coefficients of the individual country interaction terms that were significant in these 27 regressions had been incorporated into the index this iteration was complete. Further iterations were repeated until there was convergence giving the final country slope index for the pth financial variable, I_{pi}^{CF}. Complete convergence would be achieved when no Z_{pmi} term was significant at the 5% level for any country in (17) in a full iteration. Convergence may also be achieved even if interaction variables can be added with significance between iterations if the change in the index is *small* between iterations (to some tolerance level).[15] We found that 999 iterations was sufficient for all but the liquidity index to achieve complete convergence or make the changes between the values in the indices sufficiently small to conclude that they had converged.[16] For the liquidity index there is non-convergence such that the index is not the same between adjacent iterations but is exactly the same for every other iteration. In this case we tried both possible indices for liquidity in our regressions.[17]

3. Empirical Results

In this section we discuss two broad sets of results for the determinants of bank ratings. The first set allows heterogeneity to the extent that intercept and slope coefficients are different for "old" and "new" EU countries by employing shift dummy variables. The second set of results allows intercepts and slopes to be different for all countries (using index of indicator variables). For both sets we report a general model and one favoured parsimonious specification obtained using a cross-sectional variant of the general-to-specific methodology.[18] When there was ambiguity over which model to favour we selected the model with the lowest SBC. In all cases the favoured parsimonious models only include variables that are individually significant according to z-statistics and jointly significant according to a likelihood ratio test, denoted LR statistic. The restrictions placed on the general model to obtain the parsimonious model cannot be rejected according to a likelihood

[15] We regard convergence to be achieved if the percentage change in the maximised value of the likelihood function does not exceed 0.01% between two adjacent iterations.

[16] The indices for assets, operating expenses to operating income and other operating income to assets converge completely by the 999th iteration. The indices for equity, net interest margin and return on assets almost completely converge by the 999th iteration in the sense that the index changes by a very small amount. The percentage changes in the maximised value of the log-likelihood function between the 998th and 999th iteration are 0%, 0.00006% and 0.00006% for these three variables, respectively, which is well below the tolerance level of 0.01% that we set.

[17] For the liquidity index the value of the index was exactly the same between adjacent iterations for all countries except for Luxembourg. For this country, the value of the index was 2.589 in the first iteration, –1.046 in the second iteration, 2.589 in the third iteration, –1.046 in the fourth iteration and so on. We used the index that produced the best fit in our experiments, using the 998th iteration (where the value for Luxembourg is –1.046). Plots of the 998th and 999th iterations of the index for each of the 7 financial variables are available from the authors upon request.

[18] In this method we first delete all variables with z-statistics below one (or, exceptionally, 0.5 if the z-statistics are very small for a large number of variables) and apply a Likelihood Ratio (LR) test relative to the general model. If the restrictions cannot be rejected, we delete all variables with z-statistics below 1.5 and then all explanatory factors with z-statistics below 1.96 (applying all LR tests relative to the general model). If any LR test for joint restrictions is rejected, we experiment to find the variable(s) that cause this rejection and retain it (them) in the model.

ratio test [LR(general→favoured)]. The favoured parsimonious models will yield more efficient inference relative to the general model and so they are used for inference.

The ordered probit regression results that potentially allow shifts between "old" and "new" EU countries are presented in Table 1. The model reported in the column headed "No shift" in Table 1 contains no coefficients that shift for "new" EU countries (all the coefficients are the same for all countries). In the favoured model all the significant coefficients have plausible signs. That is, liquidity has a positive effect on ratings: banks with greater liquidity have a higher rating; the natural log of assets has a positive effect on ratings: banks with a larger size of assets have a higher rating; the net interest margin (NIM) has a positive correlation with ratings: a bank with a higher margin has a higher rating.[19] Further, operating expenses to operating income (OE_OI) has a negative correlation with a bank's rating: a bank with a greater ratio of operating expenses to operating income has a lower rating. All other variables are excluded from the favoured specification because they were insignificant in the general model. This benchmark model's percentage of correct predictions is 33.6% which exceeds the predictive accuracy of 10% (given 10 rating categories) expected if the ratings were assigned randomly. Hence, the model adds predictive performance that is 22.6 percentage points greater than that obtained by chance.

The favoured model in the column headed "Intercept shift" in Table 1 contains the intercept dummy variable that shifts for "new" EU countries, D_i^{New}, but no slope coefficient shift variables. The same financial variables as for the "No shift" model are significant and have the same plausible coefficient signs, while the shift in the intercept is significant and negatively signed. The latter implies that, given the financial variables, "new" EU countries receive a systematically lower rating than "old" EU countries.[20] This may reflect, for example, higher country risk and/or regulatory and legal deficiencies in "new" EU countries and confirms our hypothesis that the country of origin is an important determinant of a bank's rating. This model's percentage of correct predictions is 37.4%, thus allowing the intercept to

[19] A high NIM contributes to a bank's profitability and enables them to build up sufficient reserves/provisions for potential losses.
[20] It should be emphasised that we cannot interpret the magnitude of the coefficient on the intercept shift term as indicating by how much, on average, ratings are lower (ceteris paribus) in "new" EU countries because the coefficients are not marginal effects.

shift notably increases the model's predictive performance relative to our benchmark model.[21]

The favoured model in the column headed "All shift" of Table 1 contains variables that allow both the intercept and slope coefficients to shift depending upon whether the nation is an "old" EU or "new" EU country. Six "non-shift" variables are significant (equity, liquidity, ln(Assets), NIM, OE_OI and ROA) and their coefficients represent these variable's associations with ratings for "old" EU countries. Seven of the "shift" variables are significant (intercept, equity, liquidity, ln(Assets), NIM, OOIA and ROA) which indicates that the influence of these variables on ratings is different for "new" EU countries and "old" EU countries.[22] The model's percentage of correct predictions is 39.6% and demonstrates that allowing slopes to shift as well as the intercept further increases the model's predictive performance.[23] The negative coefficient on the intercept shift term suggests that, as for the previous model, "new" EU countries have systematically lower ratings than "old" EU countries after the effects of financial variables have been taken into account. Further, the significance of the slope shift variables' coefficients demonstrates that bank ratings responses to financial variables are different for "old" and "new" EU countries. This implies that RA's determine ratings differently for "old" and "new" EU countries in terms of banks' financial positions.

Table 2 reports the slope coefficients and t-ratios for "old" and "new" EU countries implied by the general and favoured specifications of the models reported in Table 1 under the heading "New EU intercept and slope shift". From the results corresponding to the favoured specification, 5 of the 6 significant coefficients have the expected signs for the "old" EU countries. An increase in liquidity, assets, net interest margin and return on assets will have a positive impact on ratings whereas an increase in operating expenses relative to operating income has a negative effect on ratings. All of these relations are plausibly signed. However, the negative correlation of equity and ratings is unexpected. One possible rationalisation is that banks use equity to create a buffer against possible loss or non-

[21] The other reported measures of fit, pseudo R^2 and SBC, confirm this increase in fit and, being broader measures of fit, help guard against the result arising because the former measure focuses only on whether a model predicts with complete accuracy or not.

[22] The likelihood ratio statistics indicate that these shift variables are jointly significant, confirming that the coefficients for "old" and "new" EU countries are different for all of these variables.

[23] The other reported measures of fit, pseudo R^2 and SBC, confirm this increase in fit.

performing assets.[24] Thus, a higher equity to assets ratio may indicate potential problems with asset quality, which is reflected in a lower rating.[25]

For "new" EU countries 3 of the 4 significant coefficients of the favoured model reported in Table 2 have the expected signs. Increases in assets and operating income to assets have a positive impact on ratings whilst an increase in operating expenses relative to operating income has a negative effect on ratings. In contrast, the negative correlation of return on assets with a bank's rating is not expected.[26] However, the coefficient is only just significant and may be due to a Type-I error (of which there is a 5% chance given our chosen significance level). Indeed, this finding of a positive coefficient on return on assets is not repeated in any other regressions and may, therefore, be regarded as a fragile result.

The results of the favoured model reported in Table 2 provide clear evidence that ratings are determined differently for "old" and "new" EU countries. The coefficient for "new" EU countries is significantly larger than for "old" EU countries for equity, assets and operating income. Conversely, the coefficient for "new" EU countries is significantly smaller than for "old" EU countries for liquidity, net interest margin and return on assets. Only for operating expenses to operating income are the coefficients the same for "old" and "new" EU countries.

Table 3 reports results where heterogeneous intercepts and slopes (for the financial covariates) are allowed for all countries and not just for the "new" and "old" EU country groupings. The models reported in the column headed "Intercept heterogeneity" contain the intercept country index but no country indices for the covariates' slopes. From the favoured model that allows intercept heterogeneity only we see that all significant coefficients have expected signs except equity. Date, liquidity, assets, net interest margin and operating income have plausible positive effects on ratings while operating expenses has a plausible negative correlation with a bank's rating. As before, equity has an unexpected negative impact on ratings suggesting that this may not be a fragile result.[27] It is particularly noteworthy that the intercept country index is highly significant and its inclusion in the model raises the model's percentage of correct predictions substantially (compared with the models reported in Table

[24] Until recently (before the crisis) equity (or capitalisation) was not a problem in banking.
[25] In transition economies it has been essential that banks build up high equity because of higher risk, although we do not find a negative correlation between ratings and equity for "new" EU countries.
[26] Return on assets is an indicator of profitability. In this specific case high profitability can be considered as a weakness that is associated with imprudent lending policies. In other words, a high profit may result from reckless lending. This would be especially relevant for "new" EU countries.
[27] A higher equity to assets ratio may be an indication of potential problems with asset quality which is reflected in a lower rating.

1) to 48.0%.[28] This suggests that country-specific factors, beyond those captured by financial covariates, are very important determinants of ratings.

The models reported in the column headed "All heterogeneity" of Table 3 contain both heterogeneous intercept and slope indices. The same non-index covariates as reported in the favoured model under the "Intercept heterogeneity" column are significant, except for Date, and have the same coefficient signs. The index variables that are significant are for the intercept, liquidity and operating expenses: these are the only variables that exhibit significant coefficient heterogeneity. The percentage of correct predictions is 50.5%, which suggests that adding financial covariate indices (giving slope heterogeneity) raises the predictive performance by 2.5 percentage points relative to the model only allowing intercept heterogeneity.

The values of the intercept coefficients from the intercept country index are given in Table 4. All of the countries have different intercepts, indicating that all countries' ratings contain a country-specific element. All of the "old" EU countries have larger intercepts than the "new" EU countries, indicating that country-specific factors lower "new" EU countries' ratings relative to "old" EU nations, which confirms our initial hypothesis. However, it is worth emphasising that within "old" and "new" EU country groupings there is intercept heterogeneity. Hence, factors such as sovereign risk and country differences in the legal and regulatory frameworks in which banks specifically operate affect the ratings at the individual country level. Whilst we confirm that "new" EU countries have lower ratings than "old" EU countries (after controlling for financial variables) our results emphasise that ratings do not simply differ by "old" and "new" EU country cohorts.

The country-specific coefficients for the liquidity and operating expenses to operating income variables are reported in Table 5. All of the countries' coefficients have the expected signs, except for Romania's liquidity coefficient which is relatively small in magnitude, being virtually zero. With the exception of Romania (and Spain) "new" EU countries tend to have larger coefficients for both variables compared with "old" EU countries. Further, ratings tend to be more sensitive to liquidity for "new" EU countries relative to "old" EU countries, while ratings tend to be less responsive to the ratio of operating expenses to operating income for "new" EU countries compared with "old" EU countries. Whilst there is some heterogeneity for both variables, many coefficients are the same. That is, for 16 out of 27 countries the

[28] This intercept index variable improves predictive performance relative to a model with no heterogeneity or shifts by 14.4 percentage points. That is, the model headed "Intercept heterogeneity" in Table 3 has a predictive performance of 48.0% compared with the model headed "No shift" in Table 1 where 33.6% of predictions are correct.

coefficients are the same for liquidity and for 13 out of 27 countries they are the same for operating expenses. We note that only two financial variables show coefficient heterogeneity and within these variables many of the different countries' parameters are the same, which contrasts with the intercept index which indicates a different value for all countries. It therefore appears that the main country heterogeneity comes from the intercept variable and only a small part comes from the different country responses of ratings to financial variables.

Further, recall that the predictive performance of the benchmark model containing no heterogeneous (or shifting) coefficients is 33.6%. Thus, the incorporation of a heterogeneous intercept increases this performance by 14.4 percentage points to 48.0%. Adding indices for both heterogeneous slopes and a heterogeneous intercept raises the model's predictive accuracy to 50.5%, which is a relatively modest increase of 2.5 percentage points (compared with the model containing a heterogeneous intercept). This suggests that most of the improvement in fit comes from adding a heterogeneous intercept and only a small percentage from the addition of heterogeneous slopes. Thus, the heterogeneous intercept appears to be a crucial determinant of ratings and likely captures differences in factors such as sovereign risk and the legal and regulatory framework across all countries. The comparatively limited evidence in favour of slope heterogeneity is suggestive of only modest differences in the way banks are rated according to their financial positions across countries.

To provide a final assessment of our model we consider whether the favoured model that allows for intercept and slope heterogeneity (reported in the last column of Table 3) has constant parameters through time. Ten of the new EU countries joined in 2003 while two (Bulgaria and Romania) joined in January 2007 giving rise to the possibility of changes in the ratings assignment equations around these times. Further, the international banking crisis that began in the middle of 2007 (which the rating agencies reacted to by downgrading several banks) provides an additional reason for structural change after 2007. We therefore conduct likelihood ratio tests of parameter constancy [denoted LR(time shift)] using dummy variables to allow coefficient shifts in each of the years from 2003 to 2008 in Table 6. The column headed Intercept tests for a change in intercept only, the column headed Slopes tests for shifts only in the slope coefficients, while the column headed Slopes and Intercepts tests for structural change in both intercepts and slopes of the model. We also report the pseudo R^2, SBC and percentage of correct predictions of the unrestricted model (allowing for structural changes) used in the tests.

The LR tests indicate clear evidence of coefficient changes with 15 of the 18 tests rejecting parameter constancy at the 5% level.[29] To ascertain how much benefit modelling these coefficient shifts yield we consider the fit of the models allowing for time shifts relative to a baseline model that does not (the favoured model reported in the last column of Table 5). The pseudo R^2 is at least as large as the baseline model (0.259) for all 18 models that allow shifts with the largest being 0.277 for the model allowing shifts in both intercept and slopes in 2003. However, this measure would be expected to rise when the shift variables are added (even if they were not significant) and so this is not a particularly informative measure for this purpose. The SBC, which trades of fit against the number of coefficients in the model, may be more useful. Only 5 of the 18 models have a lower SBC than the baseline model (2.777) with the smallest (by far) SBC being 2.771 for the model with a shift in both intercept and slope in 2003.

The percentage of correct predictions is an especially useful measure in this context because it provides an interpretable comparison of the different models performance. According to this measure 4 of the 18 specifications that model parameter shifts through time have greater performance than that of the baseline model. The percentage of correct predictions rises from 50.514% for the baseline model to 50.599% for the models with just an intercept shift and with both an intercept and slope shift in 2008, and to 50.685% for the model with just an intercept shift in 2003 and the model with just a slope shift in 2008. The increase in predictive performance from modelling these time shifts is, at best, 0.171 percentage points, which is a very modest rise. Hence, while the tests for parameter constancy through time suggest evidence for significant shifts, the benefit from modelling these changes through time is very small. We therefore believe that the inference from our baseline model is informative. To the extent that there are changes in the coefficients through time they most likely occur in 2003 which coincides with the accession of the first 10 of the "new" EU countries considered here and/or 2008, which is just after the accession of the last two "new" EU countries (Bulgaria and Romania) and the emergence of the international banking crisis.

[29] The tests that could not reject parameter constancy were those that only allowed an intercept shift in the years 2005, 2006 and 2007.

4. Conclusions

Our models of EU country ratings show that ratings are determined by financial variables and that these covariates have the expected coefficient signs except for equity. We suggest that the explanation for this latter result may be that a higher equity to assets ratio can be an indication of potential problems with asset quality which is reflected in a lower rating. Country-specific factors (in the form of heterogeneous intercepts) are a crucial determinant of ratings. Whilst "new" EU countries typically have lower ratings than "old" EU countries, after controlling for financial variables, it should be emphasised that all countries have significantly different intercepts. This intercept heterogeneity confirms our initial hypothesis that country-specific factors, beyond those captured by banks' financial positions, influence ratings and may reflect differences in country risk and the legal and regulatory framework that banks face (such as foreclosure laws).

There may be some differences across countries in the assignment of ratings due to the liquidity and operating expenses to operating income variables. There is some evidence that ratings are typically more responsive to liquidity and less sensitive to operating expenses for "new" EU countries compared with "old" EU countries, although differences in assigning ratings according to financial variables across countries are relatively modest. However, it is clear that the primary country heterogeneity in ratings arises from the intercept rather than from the slopes. Nevertheless, construction of slope heterogeneity indices is a novel development in the methodology of producing index-of-indicator variables.

Whilst there is evidence that parameters may not be constant through time there is little benefit to modelling these coefficient changes in terms of the improved predictive performance. The shifts in coefficients most likely take place in 2003, which coincides with the accession of 10 of the "new" EU countries, and/or 2008 which is just after the accession of Bulgaria and Romania to the EU and when the emergence of the international banking crisis became apparent. The latter may reflect ratings agencies' reaction to the discovery of various banks having substantially poorer financial positions than previously expected.

References

Altman, Edward, and Herbert, A. Rijken, “How Rating Agencies Achieve Rating Stability”, *Journal of Banking & Finance* 28 (2004): 2679-2714.

Altman, Edward, I. and Anthony, Saunders, “Credit risk measurement: Developments over the last 20 years”. *Journal of Banking and Finance* 21(1998): 1721–1742.

Altman, Edward, *The Z-Score Bankruptcy Model: Past, Present, and Future*, Wiley, New York, 1977.

Amato, Jeffery, D. and Craig, H. Furfine, “Are Credit Ratings Procyclical?”, *Journal of Banking and Finance* 29 (2004): 2641–2677.

Caporale, Guglielmo, M., Roman, Matousek, and Chris Stewart, C. “Rating Assignments: Lessons from International Banks”, DIW Berlin Discussion Paper No. 868, 2009. Available at SSRN: http://ssrn.com/abstract=1431384

D. Feng, C. Gourieroux, J. Jasiak, “The ordered qualitative model for credit rating transitions”, *Journal of Empirical Finance* 15 (2008): 111-130.

Greene William, H., *Econometric Analysis*, Pearson, Prentice Hall, 6th edition, 2008.

Grunert, Jens, Lars, Norden and Martin, Weber, The role of non-financial factors in internal credit ratings, *Journal of Banking & Finance* 29 (2005): 509-531.

Hendry David, F. and Carlos, Santos, “Regression models with data-based indicator variables” *Oxford Bulletin of Economics and statistics* 67 (2005): 571 – 595.

Hendry, David, F., “Modelling UK Inflation, 1875 – 1991” *Journal of Applied Econometrics*, 16 (2001): 255 – 275.

Huang, Zan, Hsinchun Chen, Chia-Jung Hsu, Wun-Hwa Chen, Soushan Wu. Credit rating analysis with support vector machines and neural networks: a market comparative study, *Decision Support Systems*, 37 (2004): 543-558.I

Kamstra, Mark, Peter, Kennedy, and Teck-Kin, Suan, “Combining bond rating forecasts using logit”, *The Financial Review* 37 (2001): 75-96.

Kim, Kee, S., “Predicting bond ratings using publicly available information”, *Expert Systems with Applications* 29 (2005): 75-81.

Kolari, James, D., Dennis, Glennon, Hwan, Shin and Michele, Caputo, “Predicting large US commercial bank failures”, *Journal of Economics and Business* 54 (2002): 361–387.

Kolari, James, Michele, Caputo, Drew, Wagner, “Trait recognition: An alternative approach to early warning systems in commercial banking”, *Journal of Business Finance and Accounting* 23 (1996): 1415–1434.

Lee, Young-Chan, “Application of support vector machines to corporate credit rating prediction”, *Expert Systems with Applications* 33 (2007): 67–74.

Levich, Richard, M., Giovanni, Majnoni, and Carmen, Rinhart, Ratings, Rating and Agencies and the Global Financial System, Kluwer Publishing, 2002.

Manzoni, Katiuscia, “Modeling Eurobond credit ratings and forecasting downgrade probability”, *International Review of Financial Analysis* 13 (2004): 277-300.

Meyer, Paul, A., Howard, W., Pifer, “Prediction of bank failures”, *Journal of Finance* 25 (1970): 853–868.

Ohlson, James, A., "Financial ratios and the probabilistic prediction of bankruptcy", *Journal of Accounting Research* 18 (1980): 109–131.

Portes, Richard, "Ratings agency reform", Vox, 22 January, 2008, http://www.voxeu.org/index.php?q=node/887

Stefanescu, Catalina, Radu Tunaru and Stuart Turnbull "The Credit Rating Process and Estimation of Transition Probabilities: A Bayesian Approach", *Journal of Empirical Finance* 16 (2009): 216-234.

Table 1: Bank ratings probit regressions with new EU coefficient shift

	No shift		New EU intercept shift		New EU intercept and slope shift	
Variables (expected sign)	Gen	Fav	Gen	Fav	Gen	Fav
$Date$	–0.002 (–0.229)		0.014 (1.276)		0.018 (1.509)	
$Equity_{t-1}$ (+)	–0.572 (–0.631)		–1.237 (–1.023)		–4.216 (–2.277)	–4.047 (–2.252)
$Liquidity_{t-1}$ (+)	1.301 (8.049)	1.327 (8.354)	1.285 (7.358)	1.336 (7.714)	1.118 (5.735)	1.143 (5.946)
$\ln(Assets)_{t-1}$ (+)	0.243 (14.430)	0.249 (15.683)	0.177 (8.332)	0.183 (9.030)	0.181 (6.944)	0.181 (6.929)
NIM_{t-1} (–/+)	1.672 (1.560)	1.867 (2.115)	5.694 (4.493)	5.721 (4.780)	6.052 (4.032)	5.702 (3.953)
OE_OI_{t-1} (–)	–1.461 (–10.680)	–1.547 (–13.917)	–1.342 (–6.874)	–1.517 (–8.748)	–1.119 (–5.615)	–1.182 (–6.172)
$OOIA_{t-1}$ (+)	–13.388 (–1.693)		8.993 (1.271)		–5.319 (–0.476)	
ROA_{t-1} (+)	4.593 (1.110)		8.725 (1.355)		43.807 (4.000)	42.302 (3.976)
$Intercept\_New$			–1.548 (–14.163)	–1.485 (–14.455)	–0.983 (–1.609)	–1.356 (–2.674)
$Equity\_New_{t-1}$					7.039 (2.989)	6.681 (2.902)
$Liquidity\_New_{t-1}$					–1.350 (–2.870)	–1.478 (–3.273)
$\ln(Assets)\_New_{t-1}$					0.127 (2.801)	0.121 (2.790)
NIM_New_{t-1}					–6.814 (–2.778)	–7.571 (–3.231)
$OE\_OI\_New_{t-1}$					–0.637 (–1.126)	
$OOIA\_New_{t-1}$					33.272 (2.469)	24.723 (3.546)
ROA_New_{t-1}					–59.774 (–4.291)	–50.554 (–4.735)
Fit Measures						
% correct	33.390	33.647	37.158	37.414	39.555	39.555
Pseudo R^2	0.096	0.095	0.142	0.140	0.160	0.159
SBC	3.354	3.334	3.197	3.179	3.176	3.161
LR statistic	405.272 [0.000]	401.090 [0.000]	596.398 [0.000]	588.520 [0.000]	670.413 [0.000]	666.545 [0.000]
LR(general→favoured)		4.183 [0.382]		7.879 [0.096]		3.869 [0.276]
LR(slope shift)					74.015 [0.000]	73.218 [0.000]
LR(slope/intercept shift)					265.141 [0.000]	264.186 [0.000]
Observations	1168	1168	1168	1168	1168	1168

Table 1 notes. The dependent variable is a bank's rating which has ten categories that correspond to the integer values in the range of 1 to 10 and yields nine limit points, $\lambda_i,\ i = 1, 2, ..., 9$ (the intercept is not separately identified from the limit points). Z-statistics (in parentheses) are based upon Huber-White standard errors and the percentage of correct predictions (% correct) use the category with the highest probability to give the predicted rating. Also reported are the Pseudo R^2 and Schwartz's information criterion, SBC. Likelihood ratio tests for the model's explanatory power, LR Statistic, the deletion of variables from the general model to obtain the parsimonious model, LR(general→favoured) the deletion of slope shift variables, LR(slope shift), and the deletion of slope and intercept shift variables, LR(slope/intercept shift) from a model are additionally reported. Probability values are given in square parentheses. All regressions were estimated using E-Views 6.0.

Table 2: Implied slope coefficients and t-ratios of EU shift models

	General		Favoured	
Variables (expected sign)	Old EU	New EU	Old EU	New EU
Date	0.018 (1.509)			
$Equity_{t-1}$ (+)	–4.216 (–2.277)*	2.823 (1.917)	–4.047 (–2.252)*	2.634 (1.829)
$Liquidity_{t-1}$ (+)	1.118 (5.735)*	–0.232 (–0.542)	1.143 (5.946)*	–0.336 (–0.818)
$\ln(Assets)_{t-1}$ (+)	0.181 (6.944)*	0.309 (7.773)*	0.181 (6.929)*	0.302 (8.067)*
NIM_{t-1} (–/+)	6.052 (4.032)*	–0.762 (–0.378)	5.702 (3.953)*	–1.869 (–1.011)
OE_OI_{t-1} (–)	–1.119 (–5.615)*	–1.756 –(3.208)*	–1.182 (–6.172)*	–1.182 (–6.172)*
$OOIA_{t-1}$ (+)	–5.319 (–0.476)	27.953 (3.684)*		24.723 (3.546)*
ROA_{t-1} (+)	43.807 (4.000)*	–15.967 (–1.890)	42.302 (3.976)*	–8.251 (–1.991)*

Table 2 notes. The (implied) coefficients and t-ratios are reported for new EU and old EU countries based upon the general and favoured regressions reported in Table 1 under the column headed "New EU intercept and slope shift". The coefficients and t-ratios for the old EU countries are exactly the same as those reported in Table 1. The coefficients for new EU countries are the sum of the coefficients on the variable of interest and its corresponding shift term. The t-ratios for new EU countries are calculated based upon the variance of the sum of a particular variable's coefficient (a) and its corresponding shift variable's coefficient (b), that is, Var(a + b) = Var(a) + Var(b) + 2Cov(ab). An asterix indicates that a variable is significant at the 5% level (using a critical value of 1.96 in absolute value).

Table 3: Bank ratings probit regressions with country heterogeneity

	Intercept heterogeneity		Intercept and slope heterogeneity	
Variables (expected sign)	Gen	Fav	Gen	Fav
Date	0.026 (2.489)	0.026 (2.448)	0.022 (1.714)	
$Equity_{t-1}$ (+)	–3.447 (–3.704)	–3.142 (–3.537)	–3.518 (–2.770)	–3.272 (–2.723)
$Liquidity_{t-1}$ (+)	0.541 (3.212)	0.569 (3.424)	0.380 (1.903)	0.426 (2.370)
$\ln(Assets)_{t-1}$ (+)	0.233 (13.367)	0.234 (13.461)	0.297 (9.256)	0.290 (9.248)
NIM_{t-1} (–/+)	4.845 (4.402)	5.219 (4.987)	3.741 (2.968)	3.539 (3.176)
OE_OI_{t-1} (–)	–1.237 (–8.795)	–1.324 (–11.365)	–1.354 (–5.884)	–1.418 (–7.434)
$OOIA_{t-1}$ (+)	19.053 (2.329)	20.178 (2.486)	14.911 (2.022)	17.271 (2.551)
ROA_{t-1} (+)	4.621 (1.101)		0.946 (0.162)	
$Intercept\_Country$	1.065 (24.159)	1.065 (24.159)	1.065 (19.883)	1.050 (22.507)
$Equity\_Country_{t-1}$			0.00004 (1.570)	
$Liquidity\_Country_{t-1}$			0.135 (1.161)	0.299 (3.332)
$\ln(Assets)\_Country_{t-1}$			2.166 (1.294)	
$NIM\_Country_{t-1}$			–0.00003 (–1.088)	
$OE\_OI\_Country_{t-1}$			0.217 (1.964)	0.224 (2.475)
$OOIA\_Country_{t-1}$			–0.0001 (–0.201)	
$ROA\_Country_{t-1}$			–0.000001 (–0.768)	
Fit Measures				
% correct	48.116	48.031	50.086	50.514
Pseudo R^2	0.248	0.248	0.261	0.259
SBC	2.815	2.810	2.812	2.777
LR statistic	1042.631 [0.000]	1041.420 [0.000]	1095.051 [0.000]	1086.883 [0.000]
LR(general→favoured)		1.211 [0.271]		8.168 [0.318]
LR(slope heterogeneity)			52.420 [0.000]	51.460 [0.000]
LR(slope/intercept heterogeneity)			689.779 [0.000]	682.916 [0.000]
Observations	1168	1168	1168	1168

Table 3 notes. The dependent variable is a bank's rating which has ten categories that correspond to the integer values in the range of 1 to 10 and yields nine limit points, λ_i, $i = 1, 2, ..., 9$ (the intercept is not separately identified from the limit points). Z-statistics (in parentheses) are based upon Huber-White standard errors and the percentage of correct predictions (% correct) use the category with the highest probability to give the predicted rating. Also reported are the Pseudo R^2 and Schwartz's information criterion, SBC. Likelihood ratio tests for the model's explanatory power, LR Statistic, the deletion of variables from the general model to obtain the parsimonious model, LR(general→*) the deletion of slope shift country variables, LR(slope heterogeneity), and the deletion of slope and intercept country variables, LR(slope/intercept heterogeneity) from a model are additionally reported. Probability values are given in square parentheses. The variables corresponding to the country shift are all determined after 999 iterations except the one for liquidity, which alternated between two different forms - we used the form corresponding to the 998th iteration. All regressions were estimated using E-Views 6.0.

Table 4: Heterogeneous intercept (country weights)

Country	Weight	Country	Weight
Old EU		***New EU***	
Luxembourg	3.493	Estonia	0.653
Netherlands	2.527	Slovakia	0.590
UK	2.485	Malta	0.570
Denmark	2.450	Hungary	0.344
Spain	2.357	Cyprus	0.338
Sweden	2.137	Slovenia	0.284
Ireland	2.098	Czech R	-0.172
Portugal	1.851	Poland	-0.196
Finland	1.723	Bulgaria	-0.204
Belgium	1.559	Romania	-0.211
Austria	1.440	Lithuania	-0.227
Italy	1.263	Latvia	-0.601
France	1.182		
Germany	0.727		
Greece	0.670		

Table 4 notes. The coefficient of the individual countries embodied in the index of indicators variable, $Intercept\_Country$, are given. The coefficients are ranked from highest to lowest value.

Table 5: Heterogeneous slopes

<table>
<tr><th colspan="2">Liquidity</th><th></th><th colspan="2">Oe_oi</th></tr>
<tr><td>Malta</td><td>0.900</td><td></td><td>Sweden</td><td>-1.696</td></tr>
<tr><td>Lithuania</td><td>0.836</td><td></td><td>Denmark</td><td>-1.695</td></tr>
<tr><td>Latvia</td><td>0.802</td><td></td><td>Finland</td><td>-1.647</td></tr>
<tr><td>Bulgaria</td><td>0.676</td><td></td><td>Romania</td><td>-1.642</td></tr>
<tr><td>Slovenia</td><td>0.620</td><td></td><td>Germany</td><td>-1.601</td></tr>
<tr><td>Spain</td><td>0.533</td><td></td><td>Austria</td><td>-1.591</td></tr>
<tr><td>Austria</td><td rowspan="16">0.426</td><td></td><td>France</td><td>-1.587</td></tr>
<tr><td>Belgium</td><td></td><td>Italy</td><td>-1.577</td></tr>
<tr><td>Cyprus</td><td></td><td>Belgium</td><td rowspan="13">-1.418</td></tr>
<tr><td>Czech Republic</td><td></td><td>Cyprus</td></tr>
<tr><td>Estonia</td><td></td><td>Czech Republic</td></tr>
<tr><td>Finland</td><td></td><td>Estonia</td></tr>
<tr><td>France</td><td></td><td>Greece</td></tr>
<tr><td>Greece</td><td></td><td>Ireland</td></tr>
<tr><td>Hungary</td><td></td><td>Luxembourg</td></tr>
<tr><td>Ireland</td><td></td><td>Netherlands</td></tr>
<tr><td>Italy</td><td></td><td>Poland</td></tr>
<tr><td>Netherlands</td><td></td><td>Portugal</td></tr>
<tr><td>Poland</td><td></td><td>Slovakia</td></tr>
<tr><td>Portugal</td><td></td><td>Spain</td></tr>
<tr><td>Slovakia</td><td></td><td>UK</td></tr>
<tr><td>UK</td><td></td><td>Slovenia</td><td>-1.283</td></tr>
<tr><td>Sweden</td><td>0.276</td><td></td><td>Bulgaria</td><td>-1.215</td></tr>
<tr><td>Denmark</td><td>0.198</td><td></td><td>Lithuania</td><td>-1.194</td></tr>
<tr><td>Germany</td><td>0.132</td><td></td><td>Malta</td><td>-1.191</td></tr>
<tr><td>Luxembourg</td><td>0.114</td><td></td><td>Hungary</td><td>-1.184</td></tr>
<tr><td>Romania</td><td>-0.057</td><td></td><td>Latvia</td><td>-1.170</td></tr>
</table>

Table 5 notes. The coefficients for each individual country implied by the financial variables' parameters and the index of indicator variables, $Liquidity\_Country_{t-1}$ and $OE\_OI\_Country_{t-1}$, are given. These are constructed as the coefficient on the pth financial variable, $\hat{\beta}_p^F$, and the product of the pth variable's index, I_{pi}^{CF}, and its associated coefficient, $\hat{\beta}_p^{CF}$, that is, as, $\hat{\beta}_p^F + \hat{\beta}_p^{CF} I_{pi}^{CF}$. The coefficients are ranked from the highest to lowest value for liquidity and lowest to highest for operating expenses to operating income.

Table 6: Tests for parameter constancy through time

Year	Statistic	Intercept	Slope	Intercept and slopes
2003	Pseudo R^2	0.261	0.267	0.277
	SBC	2.774	2.800	2.771
	% Correct	50.685	49.829	49.572
	LR(time shift)	10.266 [0.001]	36.616 [0.000]	77.278 [0.000]
2004	Psuedo R^2	0.261	0.266	0.276
	SBC	2.775	2.806	2.774
	% Correct	49.829	49.572	49.229
	LR(time shift)	9.412 [0.002]	29.939 [0.000]	74.110 [0.000]
2005	Pseudo R^2	0.259	0.264	0.273
	SBC	2.781	2.812	2.786
	% Correct	49.572	48.973	49.829
	LR(time shift)	1.988 [0.159]	21.927 [0.009]	60.058 [0.000]
2006	Pseudo R^2	0.259	0.263	0.273
	SBC	2.782	2.815	2.786
	% Correct	50.086	49.229	49.829
	LR(time shift)	0.424 [0.515]	19.530 [0.021]	59.874 [0.000]
2007	Pseudo R^2	0.259	0.263	0.269
	SBC	2.782	2.816	2.800
	% Correct	50.171	49.914	50.257
	LR(time shift)	0.560 [0.454]	17.457 [0.042]	43.557 [0.000]
2008	Pseudo R^2	0.260	0.263	0.266
	SBC	2.776	2.815	2.811
	% Correct	50.599	50.685	50.599
	LR(time shift)	7.861 [0.005]	19.430 [0.022]	30.148 [0.001]

Table 6 notes: statistics assessing the constancy of coefficients in the favoured specification that allows both intercept and slope heterogeneity (reported in the final column of Table 3) are given. A dummy variable that takes the value of unity in the date specified in the column headed Year (as well as all subsequent periods) and is zero otherwise is added to this model and various statistics relating to this dummy-augmented specification are reported in the column headed Intercept. The same statistics for the favoured model under current consideration augmented by slope-shift terms (the time dummy is interacted with each explanatory variable in the model) are reported in the column headed Slopes. Similarly, statistics are also reported for the favoured model augmented by both a time-intercept shift dummy as well as slope-shift terms in the column headed Intercept and slopes. The reported statistics are the pseudo R^2, SBC and percentage of correct predictions (% correct) as well as a likelihood ratio test [denoted LR (time shift)] for the deletion of all time-dummy variables from the time augmented models. The probability values for this likelihood ratio test are given in squared parentheses.